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Efficiency of second-generation biofuel crop subsidy schemes: Spatial heterogeneity and policy design

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ABSTRACT

Policy schemes that aim to stimulate the cultivation of biofuel crops typically ignore the spatial heterogeneity in costs and benefits associated with their production. Because of spatial heterogeneity in biophysical, and current agricultural production factors, potential gains from stimulating biofuel crops are non-uniformly distributed across space. This paper explores implications of this type of heterogeneity for the net benefits associated with different subsidy schemes. We present a simple framework based on discounted cash flows, to assess potential gains from introducing the notion of heterogeneity into stimulation schemes. We show that agricultural subsidy spending can be reduced in a Pareto efficient way and simultaneously improve the total stimulation potential of biofuel policies, when schemes: 1) are production based instead of land based; 2) accommodate differences in opportunity costs, and 3) target sites where subsidies for conventional agricultural land-use types are high. These results are robust for a range of different bioenergy prices and the relative gains of addressing these key elements in policy compared to conventional stimulation schemes increase with lower bioenergy prices, and are largest when low prices coincide with high emission reduction ambitions.

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1. Introduction

The constraints of finite natural resources in combination with concerns about global warming have led researchers and policymakers to pay increased attention to the topic of sustainable energy policies and the reduction of greenhouse gas emissions. The switch to biofuels as a transportation fuel source has been put forward as a possible contribution to carbon emission reduction plans and overall sustainable energy strategies [25,49,38]. Second-generation ethanol production from lignocellulosic material is generally considered to avoid (partly) social and environmental impacts linked to biofuel production [52], and could become a key contributor to emission reductions. Although lignocellulosic ethanol production from biomass may become a suitable option in the future, large-scale production is not economically feasible at present and stimulation policies have to be implemented to achieve future bioenergy usage ambitions [67]. Many countries are struggling to achieve 2020 goals for fuel standards. In 2015, the average European blending share of crop based ethanol and biodiesel was estimated at respectively 3.3% and 4.3%, and at about 0.6% for non-food based biofuels [29]. Though the sector has achieved considerable growth worldwide in recent years [51], the strong decline in crude oil prices that started in the second half of 2014 has put the competitiveness of biofuels under severe pressure, and the current policy ambitions are not expected to lead to significant higher production in the next decade [44]. Because economic benefit is arguably the most important incentive for adoption, efficient subsidy strategies are of relevance for the future of biofuels and might not only be key in reaching 2020 fuel standards, but might determine when, or whether, we ever get a viable model for large scale production.

The focus of this paper is to explore possibilities to minimize subsidy spending and simultaneously increase the total stimulation potential of biofuel policies, while maintaining the income levels of farmers. Such possibilities allow for Pareto improvement with respect to the current situation as society can both save money on subsidies and gain from environmental benefits related to biofuel production, while profits of farmers would be unaffected by the subsidy reform. Reducing spending and increasing the stimulation potential of schemes can contribute to the overall cost effectiveness of policies and might strengthen the case of bioenergy production in the political arena. In past years, different studies proposed heterogeneous allocation of resources under different environmental policies, for example carbon sequestration contracts [2], air pollution emission trading programmes [31], vehicle emission abatement [42], and policies that promote investment in renewable electricity generators [26]. Current bioenergy stimulation policies typically do not recognize that there is substantial spatial variation in costs and benefits associated with biofuel crop production. This heterogeneity relates to interaction between policies stimulating the production of bioenergy, spatially heterogeneous production factors, agricultural land-use patterns, and other agricultural policies. The central thesis of this paper is that introducing the notion of spatial heterogeneity into subsidy schemes allows for more efficient allocation of subsidies, and potentially increases net social benefits by decreasing subsidy costs and increasing positive externalities. We build our analysis on the following three elements: first we assess spatial heterogeneity in Net Present Value (NPV) of current agricultural production systems; we then estimate site-specific net social costs and benefits of stimulation schemes; and finally, we compare the relative efficiency of alternative subsidy schemes in terms of associated potential net benefits. We repeat the analysis for a range of different bioenergy prices to show how the results change when the relative competitiveness of conventional land use and bioenergy production changes. We apply our analysis to explore production of a specific second-generation bioenergy crop - Miscanthus (*Miscanthus* $\times$ *Giganteus*) - in the Netherlands, a country with an advanced agricultural sector that has a high economic value per hectare. The Netherlands is currently far behind the European average for sustainable energy usage, and as we shall see in our application of the developed theory, could benefit from more effective bioenergy policy design.

The remaining part of this paper is organized as follows. In Section 2, we discuss inefficiencies that arise due to land heterogeneity. Section 3 details our methods. Section 4 describes our application to Miscanthus in the Netherlands. Section 5 presents the results, followed by a discussion and conclusion in Section 6.

2. The importance of spatial heterogeneity in agricultural policy

Agricultural systems are strongly determined by spatially heterogeneous agro-economic, socio-economic, and local biophysical conditions [15]. Spatial economic models that build upon this heterogeneity confirm that biomass is able to provide a substantial contribution to the overall energy supply. This future bioenergy potential has been assessed on the global scale [36,53], at the European level [61,12,27,28], and at national levels [5,57,62]. An overview of the different assessments and their respective strengths and weaknesses is given by [18], who point out that spatial variation in production characteristics is the most important aspect in assessing bioenergy potentials. Recent studies focusing on local opportunities for biofuel production were able to pinpoint specific areas of interest by using micro data on production characteristics [63,14]. Understanding the economic implications of spatial variability in local production factors might help researchers and policymakers in the field of environmental economics and resource management work towards more efficient forms of policy. However, existing agro-economic and bioenergy stimulation policies often do not explicitly address spatial heterogeneity and abstain from insights gained from bioenergy potential assessments.

Two examples illustrate this lack of attention to spatial aspects. The governments of Canada and the United States have proposed policies in which farmers are paid for the adoption of certain management practices to sequester carbon dioxide in agricultural soils [1,68]. In the European Union, farmers who grow bioenergy crops can apply for a standard land based subsidy [21]. Such a subsidy scheme is analogous to the proposed Canadian and United States government subsidy scheme as farmers are paid for adopting site-specific practices. Market-based incentives, however, are generally seen as more efficient than command-and-control or environmental design standard policies because there are cost-efficiency differences in abatement strategies among the entities within a sector, for example when both costs and environmental benefits differ among plots [59,55]. Efficient agricultural policies that aim to increase environmental benefits by influencing the management decisions of farmers, must therefore take into account the heterogeneity of the biophysical and economic factors that determine the agricultural system [37]. Paying farmers to adopt certain management practices in a land based system, disregarding the biophysical differences among their production sites, is generally seen as inefficient [35,3,30].

We particularize by distinguishing between two types of inefficiencies in bioenergy stimulation schemes: overfunding and misallocation of funds. When a farmer produces biofuel under a (government-funded) carbon contract, the contract value is part of the farmer's private profit function. In the economic environment of an emission trading market, contract values are conditional on a spatially varying factor, that is, the quantity of biomass produced in specific locations, and an exogenous factor that is equal among farmers, the price of one unit of carbon. It follows that the income generated by farmers through carbon contracting is a monotonic transformation of the spatial distribution of production quantities, which has a direct relation not to local production costs but to the local biophysical conditions that determine biomass yields. Farmers with comparative advantages thus possibly receive aids that greatly exceed the marginal costs of bioenergy crop production, resulting in allocation of excessive funds and *ex post* inequalities.

Misallocation of funds occurs when spatial characteristics that are not part of the private profit function appear in the social welfare function. This difference can originate from both the cost and the benefit side of the economy. One mechanism through which the social cost function differs from the private cost function, is that the production of bioenergy crops can reduce subsidy distributed elsewhere in the market. Subsidies for crops are mutually exclusive, meaning that farmers can only opt for a single crop subsidy per plot at a time. Under the assumption that avoided subsidies for conventional land uses will return efficiently to society, low social costs do not necessarily coincide with low private costs in their joint spatial distribution. The possibility exists that for any given farmer, the private bioenergy production profits are below zero (a subsidy is required, disregarding the potential profits related to other land-use types), while the net social cost of sustaining the required subsidy is negative. This happens for example when farmers receive subsidies for conventional land-use types that exceed the subsidy requirements to produce bioenergy, while the private profits, after subsidy, of both alternatives are equal. In this case there is room for a Pareto-efficient reduction in conventional subsidies. Generally, if positive private opportunity costs for biomass production at a certain point in the spatial distribution coincide with negative social costs for sustaining local bioenergy production in the joint spatial distribution, possibilities for Pareto improvement exist and it could be said that society is allocating its funds to the wrong sites.

A similar issue arises on the benefit side of social welfare. Since the production of bioenergy crops is associated with positive external effects - perennial crops sequester carbon in their root systems and the use of biofuels reduces carbon emissions - a strictly positive spatial distribution of externalities exists conditional on the local biophysical conditions. This spatial distribution, part of the spatial social benefit distribution, is not internalized in the spatial distribution of private benefits. The optimal land-use patterns from a societal perspective will thus differ from patterns that arise from private decisions. Summarizing, spatial heterogeneity in local production characteristics under a policy that inadequately accounts for spatial differences leads to inefficient outcomes due to two principles:

1. A non-uniform spatial distribution of marginal production costs leads to overfunding at production sites that have comparative advantages, when subsidies are distributed uniformly across plots.
2. If the spatial distributions of social and private costs and social and private benefits differ, schemes that do not promote internalization of externalities and instead follow private optimization decisions, misallocate funds from a societal perspective.

3. Methodology

We develop a spatially explicit economic assessment strategy to evaluate potential net benefits of subsidizing bioenergy at the grid-cell level. Both the cost and the benefit side of the model build upon an explicit representation of land heterogeneity and require micro-data on biophysical conditions, market prices, and agricultural land use. By combining this information, we estimate the NPV of the currently existing agricultural land uses and of bioenergy crop production using a multiple-year time span, thus incorporating long-term decision processes related to perennial crop management and start-up investment costs. The difference in the economic performance of bioenergy crop production and conventional agricultural production types is used to determine a minimum required contract value for each plot. The net social cost of the stimulation policy is calculated by comparing the minimum required subsidies with subsidies distributed among conventional land uses. The spatial distribution of potential social benefits of bioenergy production is based on the emission offsets provided by local biomass production quantities, and the amount of carbon sequestered in the root systems of perennial crops. By comparing the net costs of subsidizing with the benefits associated with the subsidized sites, we are able to evaluate the effectiveness of different types of policies. The next section introduces the seven stimulation schemes that we shall explore in our application. Section 3.2 provides further details to the structure of the model.

Table 1
Overview of the alternative subsidy schemes distinguished in this study.

	Heterogeneous		Conventional	
	Land Based	Production based	Land based	Production based
Single focus	SFLB[1]	SFPB[2]	CLB[3]	CPB[4]
Integrated focus	IAFLB[5]	IAFBP[6]		
Minimize LUC		MLPB[7]		

[1] single focus land based.
[2] single focus production based.
[3] conventional land based.
[4] conventional production based.
[5] integrated agricultural focus land based.
[6] integrated agricultural focus production based.
[7] minimized land-use change production based.

3.1. Different spatial policies

A government that engages in bioenergy stimulation can either subsidize farmers directly through a periodical land based payment or introduce a carbon contracting system in which farmers receive funds by providing carbon emission offsets to entities, including the government, that are willing to buy such contracts to suppress their carbon rating.[1] Contracts or subsidies based on emission offsets are referred to as production based schemes as they directly relate to the quantities of produced biomass. Both types of periodical payments can be homogeneous across space, as in conventional schemes, or they can be altered to account for spatial heterogeneity. Heterogeneous subsidy schemes allocate the exact amount of funds to each farmer needed to sustain the local production of bioenergy crops.

We analyse seven alternative bioenergy stimulation schemes (Table 1) that address heterogeneity to various degrees. We first distinguish between spatially heterogeneous and conventional (homogenously distributed) subsidies. Within the category of heterogeneous subsidies, a second distinction is made between: 1) single focus (SF) schemes that subsidize plots where the local opportunity costs for biofuel production are lowest, and minimize the total funds spent on bioenergy stimulation; and 2) integrated agricultural focus (IAF) schemes that also take into account how

[1] We use contracts and subsidies somewhat interchangeably throughout the paper because we do not explicitly differentiate between types of entities, but view society as the final entity that pays for such contracts.

conventional agricultural subsidies are spatially distributed. IAF schemes aim to limit total aggregate spending on agricultural subsidies by subsidizing plots where net social costs for biofuel production stimulation are lowest. This integrated approach is more efficient as it captures reductions in the aggregate agricultural subsidy spending by decreasing the, often excessive, subsidies for other types of production. Both SF and IAF schemes offer farmers a single subsidy that does not depend on the farmer's choice of production type. Under the assumption that farmers optimize profits, and that land conversion occurs accordingly, farmers that receive less subsidy after the policy reform are reconciled by increased productivity associated with the alternative production system. So, in our simple framework, both SF and IAF schemes reduce spending in an Pareto efficient way. These stimulation strategies are particularly interesting for biofuel stimulation schemes that generate positive externalities associated with emission reductions, but the implications of the results stretch out over other conventional agricultural subsidy schemes. In a sense, heterogeneous schemes undo a policy induced market failure. By offering farmers site-specific financial support, agricultural land-use patterns are generated by profit maximization principles that follow the productivity of farmers. Under homogenous subsidies that vary per crop type, this equilibrium land-use pattern is distorted and farmers have an incentive to move away from optimum and produce crops for which their land is not suited, as long as they are sufficiently reconciled by the crop-specific subsidy.

Both heterogeneous and conventional subsidies are analysed under per-hectare and per-tonne contracts. Additionally, we analyse policy that is fully directed at minimizing land-use change by allocating subsidies on a command-and-control basis to the sites associated with highest biomass production potentials.

3.2. Spatial economic model

The model that we apply consists of several elements, and we first detail the overall structure before providing the equations. The underlying assumption of our approach is that farmers operate under optimal inputs and subsequently allocate their land between alternative crops in order to maximize their profits. We therefore, similar to other land-use allocation models, start with a profit maximization problem. From this maximization problem, we derive a simple land-use allocation rule that serves as a starting point for constructing an indifference surface conditional on site-specific subsidy levels. We then formulate restrictions for homogeneity and heterogeneity of stimulation schemes. Given these restrictions and the spatial indifference surface, we derive spatial distributions for the minimum required subsidies under heterogeneous and conventional schemes. These are compared to current subsidy spending on conventional crops to derive plot-specific social costs of sustaining the required subsidy to convert a given plot to a bioenergy production site. We separately construct a spatial distribution of external benefits associated with fossil fuel savings and carbon sequestered in the root system of the bioenergy crop using a carbon price. The site-specific net social costs of sustaining biofuel production is than compared to the benefits associated with production to map site-specific potential net benefits of biofuel production. Finally, we aggregate the local net benefits of those sites that are covered under a specific stimulation scheme to enable a comparison of the total potential benefits associated with different schemes. The remaining part of this section details all of the analysis steps.

In our simplified land-use allocation model, we view the study area as consisting of a number of production sites indexed by $i \in I$. We assume that in order to maximize their profits, farmers make a choice between two types of land use $l = [c, e]$, where c denotes conventional agricultural land use and e denotes the allocation of energy crops. The economic decision process for a multiple-year period that farmers face can thus be described as the following multi-period profit-maximization problem:[2]

$$\underset{l \in L}{\operatorname{argmax}} \Pi_i^l = \sum_{t=0}^{T} \frac{\pi_{it}^l}{(1+r)^t} \tag{1}$$

Where profits are generated according to the spatial timeseries:

$$\pi_{it}^l = p_{it}^l q_{it}^l(\varphi_{it}^l) + s_{it}^l - w_{it}^l h_{it}^l - k_{it}^l - o_{it}^l(q_{it}^l) \ \forall \ it \in \mathbb{N} \times \mathbb{Z} \tag{2}$$

Where ${p_{it}}^l$ are the plot-level prices for the vector of outputs of land-use types l at time t, ${q_{it}}^l$ is the vector of outputs, which is a function of local yield factors ${\varphi_{it}}^l$, ${w_{it}}^l$ are prices for the vector of inputs, ${s_{it}}^l$ are plot-level subsidies, ${k_{it}}^l$ are fixed costs containing start-up investments, equipment costs and yearly fixed costs, and finally ${o_{it}}^l$ are the field operation costs, which may vary with output ${q_{it}}^l$.

Let Π_i^e and Π_i^c be real variables and Π_i' denote any particular set of values of these two variables. Any such set is represented by a point in a two-dimensional Cartesian space. Let $\Pi \supseteq \Pi_i'$ be the superset of all such points and let Π^c and Π^e be the subsets of Π including points for which Π_i' produces either a conventional crop production site contained in I^c, or an energy crop production site contained in I^e. To be able to assign set membership to I^l based on Π_i^l, we require that some further logic exists. The profit maximization by land-use choice under mutually exclusive land-use types provides a rule "$A(\Pi_i')$" that defines the subset $I^e \subseteq I$. This rule "$A(\Pi_i')$" ascribes to each production site contained in I, the property of belonging to I^e or not, based on any set of values Π_i' for the two land-use types. The profit-maximization problem in Eq. (1) leads to the following rule:

$$i\{\Pi_i^e > \Pi_i^c\} \in I^e \tag{3}$$

Note that if profits would instead have been stochastic, this and subsequent results follow similarly under expected value theory if Π_i^e and Π_i^c are consistent estimates of the first moments of their stochastic counterparts. Note also that, though prices are given in a competitive market, a farmer has the ability to choose the level of inputs and that a government can choose to change ${s_{it}}^l$, such that any pair Π_i' is possible, which in turn according to the timeseries system Eqs. (1)–(3) can produce any agricultural landscape. If we keep Π_i^c constant, that is, assuming optimal private inputs and fixed conventional subsidies, $\Pi_i^e(s_{it}^e) > \Pi_i^c$ has a unique asymptotic lower bound, $\Pi_i^e(s_{it}^e) = \Pi_i^c$, on which rational farmers are indifferent between biofuel and conventional agricultural production. All sets Π_i' that produce membership in $I \backslash I^e \backslash I^c = I^0$ together constitute this spatial indifference surface on which profit maximizing farmers are indifferent between production types. From Eq. (1) it is clear that under these assumptions it is a straightforward approach to find the local subsidy values ${s_{it}}^e$ that establish this indifference surface, e.g. to find the lower bound of required subsidies to sustain biofuel stimulation.

Depending on the policy type, the spatial distribution of the bioenergy subsidy ${s_{it}}^e$ can either be spatially homogeneous $\bar{s}_{nt}^e$, which we indicate with an overbar and index by $n \in N$ with $N \subseteq [1, \ldots, |I|]$ being a subset of the ordered sequence from 1 to the cardinality of the entire set of plots, or spatially heterogeneous $\check{s}_{it}^e$, which we indicate with a check. We index by n to distinguish from heterogeneous schemes. More specifically, heterogeneous subsidies can be uniquely indexed over the entire set of plots, whereas

[2] In this paper we make use of the following notation: (discounted) summations of any symbol are given by its respective capital, e.g. $Z \equiv \sum_{i=1}^{I} z_i$, similarly for sets, capitals contain their lowercase as elements, we index variables by land-use type with a superscript such that $z^e \equiv z^{l=e}$ is identical and reads as the variable z under bioenergy production, and write constraints between braces { }, e.g. $i\{A\} \in I^A$ reads as all elements i for which rule "A" holds, are members of the set I^A".

homogenous subsidies are equal among plots and indexed by the cardinality of the set of bioenergy production sites, $n:=|I^e|$, i.e. homogenous subsidies increase as the amount of plots converted to bioenergy production sites increases. Spatially homogeneous subsidies $\bar{s}^e_{nt}$ are identical across i and must satisfy $\bar{s}^e_{i-1,nt}:=\bar{s}^e_{int}\ \forall\ i \in I$, hence we shall continue without subscripting i for spatially homogenous variables. The criterion carries that when n plots are subsidized, the marginal increase in the aggregate subsidy by subsidizing the next plot $i+1$ that is contained in an extended set of $n+1$ production sites, equals $\bar{s}^e_{n+1,t} + n(\bar{s}^e_{n+1,t} - \bar{s}^e_{nt})$. Thus, if there are differences in subsidy requirements between a newly subsidized plot and the most efficient plot of all formerly subsidized plots, the marginal increase in aggregate subsidy does not only increase by the subsidy amount required at the new plot but also by the efficiency difference multiplied by the amount of plots that already received aids. Spatially heterogeneous subsidies, on the other hand, are flexible and allow for any finite difference between subsidies at any two points within the distribution and satisfy $0 \le |\check{s}^e_{it} - \check{s}^e_{i+1,t}| < \infty$. The marginal increase in the aggregate subsidy of subsidizing the next plot $i+1$ when the subsidies are heterogeneous is just $\check{s}^e_{i+1,t}$, the subsidy required for production at the new site. The difference in the marginal increase in the aggregate homogeneous subsidy and aggregate heterogeneous subsidy is $\bar{s}^e_{n+1,t} + n(\bar{s}^e_{n+1,t} - \bar{s}^e_{nt}) - \check{s}^e_{i=n+1,t}$. The requirements of the newly subsidized plot under both schemes are equal, thus the marginal increase in total subsidy costs is given by $n(\bar{s}^e_{n+1,t} - \bar{s}^e_{nt})$ and thus depends on the amount of heterogeneity between plots that drives the difference between $(\bar{s}^e_{n+1,t} - \bar{s}^e_{n,t})$, and the size of the policy area n before increasing its extent. The marginal cost function of converting an additional production site to energy crop production under homogenous schemes, thus depends on the site-specific exogenous determinants that enter any private profit function within the entire policy area, whereas the marginal cost function under a heterogeneous scheme is just a function of local variables. In our application we shall study how the impact of heterogeneity changes as the size of the policy area grows to the size of the entire set of potential production sites $|I^e| \to |I|$.

To derive the minimum spatially homogenous subsidies $\bar{s}^e_{nt}$, it is necessary to write down the exact relationship between the total *area* of sites dedicated to bioenergy production and the decision rule of Eq. (3), so that we can determine n. Assuming optimal private inputs under both land-use types, the total bioenergy production area is given by summing over the individual sizes of the plots for which the decision rule of Eq. (3) holds.

$$Y^e = \sum_{i=1}^{I^e} y_i^e \tag{4}$$

Where $y_i{}^e$ is the individual plot size and Y^e the aggregate production size dedicated to bioenergy production. Suppose that a government aims to have a total area of Y^e devoted to the production of bioenergy crops, than Eq. (4) inversely provides the amount of required plots to achieve that level of coverage. To find the minimum spatially homogenous subsidy $\bar{s}^e_{nt}$ required to stimulate n plots, we need to establish indifference in the least efficient production site $i=j$, $j \in [1, \ldots, n]$, e.g. the production site that requires the highest aid. Thus, in the j-th plot, we need $\Pi_j^e = \Pi_j^c$ to hold and then solve for $s_{jt}{}^e$. As $\Pi_j{}^e$ is the subsidized profit, we can write it as a function of the unsubsidized profit and a subsidy component:

$$\Pi_i^e = \widetilde{\Pi}_i^e + S_i^e \tag{5}$$

where

$$S_i^e = \sum_{t=0}^{T} \frac{s_{it}^e}{(1+r)^t}$$

There are multiple solutions to $s_{it}{}^e$ in Eq. (5) as cash flows may vary throughout years, for example a lump sum in the first year can be the NPV equivalent of an annuity. The discounted total subsidy $S_i{}^e$ is, however, unique, so it follows that indifference $\Pi_j^e = \Pi_j^c$ holds when $S_j^e = \Pi_j^c - \widetilde{\Pi}_j^e$ and bioenergy subsidy is equal to the unsubsidized profit gap. Using the homogeneity rule, it follows also that the discounted total homogenous subsidy for any plot equals that of the least efficient plot $\bar{S}_n^e = S_j^e$. For any production area size Y^e containing n plots, we can write the spatially homogeneous subsidy that minimizes the aggregate subsidy as a function of the largest unsubsidized profit gap occurring in all the bioenergy production sites I^e.[3]

$$\bar{S}_n^e = \max_{i \in I^e}(\Pi_i^c - \widetilde{\Pi}_i^e) \tag{6}$$

One important result that we can directly derive from this is that within the current system, farmers are paid to withhold from innovation, and the introduction of new subsidy systems is required for any innovative crop before it can be produced on a large scale.[4]

Using the decision rule of Eq. (3), we can similarly construct a distribution of spatially heterogeneous minimum subsidies at which farmers are tangent to choosing $l=e$, by finding the exact values for $S_i{}^e$ that coincide with values of $\Pi_i{}'$ that produce set membership in I^0. Hence, to find the plot-specific discounted spatially heterogeneous minimum subsidy $\check{S}_i^e$, we need to establish indifference $\Pi_i^e = \Pi_i^c$ at all plots i. Straightforward use of Eq. (5), gives us:

$$\check{S}_i^e = \Pi_i^c - \widetilde{\Pi}_i^e \tag{7}$$

The spatial distribution of net subsidy spending is calculated as the difference between conventional subsidies and bioenergy stimulation subsidies. Net subsidy spending is what society pays to produce environmental benefits through biofuels; therefore, we will refer to it as social costs, though we do not take into account other potential costs than direct spending.

$$C_i^e = S_i^e - S_i^c \tag{8}$$

Apart from the net subsidy spending involved in bioenergy stimulation, we consider also the benefits associated with avoided carbon emissions. The potential social benefits at a specific production site are given by the benefits of emission savings and the difference between benefits from additionally sequestered carbon.

$$B_i^e = \sum_{t=0}^{T} \frac{p_\varepsilon \varepsilon^e q_{it}^e + p_\varepsilon(\sigma_{it}^e - \sigma_{it}^c)}{(1+r)^t} \tag{9}$$

Where p_ε is the carbon price, ε^e are the emissions saved per unit of bioenergy production, and $\sigma_{it}{}^l$ are the emission saving equivalents of sequestered carbon in the root system of perennial crops. Net benefits are given by the difference between social benefits and social costs.

$$\omega_i{}^e = B_i^e - C_i^e \tag{10}$$

In aggregate, we can quantify the total net benefits by summing

[3] To confirm that this indeed is a minimum, consider lowering the value of $\bar{s}^e_{nt}$ for all plots with a minor fraction just sufficient to cause $\pi_j^e < \pi_j^c$. This will only be sufficient to stimulate $n-1$ plots. Lowering the value of $\bar{s}^e_{nt}$ for one or several plots with a minor fraction will break the condition of spatial homogeneity.

[4] Note that we can similarly split up net present value profits of conventional agricultural land use $\Pi_j{}^c$. Therefore to obtain indifference in a subsidized agricultural system, $\widetilde{\Pi}_i^e = \widetilde{\Pi}_i^c \Longrightarrow S_i^e = S_i^c$, which means that any positive value for $S_i{}^c$ forms an innovation barrier, preventing bioenergy production at otherwise competitive sites, e.g., where both unsubsidized land-use types would be equally profitable.

up all the plot-level gains for sites where private profits for growing bioenergy crops exceed profits from growing conventional crops.

$$\Omega^e = \sum_{i=1}^{I^e} \omega_i^e = B_i^e - C_i^e = \sum_{t=0}^{T} \frac{p_\varepsilon \varepsilon^e q_{it}^e + p_\varepsilon(\sigma_{it}^e - \sigma_{it}^c)}{(1+r)^t} - (S_i^e - S_i^c) \quad (11)$$

In the rightside equality in Eq. (11), we see the direct relation between the spatially heterogeneous potential benefits and the spatial distribution of subsidies allocated to production sites S_i^e, where $S_i^e = \bar{S}_n^e$ for homogeneous subsidies or $S_i^e = \check{S}_i^e$ under heterogeneous subsidies schemes. It follows directly from Eq. (11) that under heterogeneous production factors, the potential gains under heterogeneous subsidies are higher than those under homogenous subsidies.[5] This should come as no surprise given the expressions of the marginal costs for converting an additional farmer derived earlier, but it is an empirically interesting matter to contrast the differences in total potential net benefits of alternative schemes using real data for a range of potential production area sizes. The straightforward equations suggest that a researcher armed with micro-data on in- and output price vectors, production costs and quantities, land-use patterns, and current subsidy schemes, is able to do just that by plugging them in Eq. (1), and evaluating the total net benefit potential under different types of policy by substituting S_i^e with values of $\check{S}_i^e$ or $\bar{S}_n^e$ and calculating Ω^e for the set of sites I^e for which the subsidy is sufficient to convert profit maximizing farmers into bioenergy crop producers. Similarly, policy-objective related benefit potentials can be calculated by summing i over the set of production sites I^e_{target} for which the total bioenergy crop production $Q^e = \sum_{t=0}^{T}\sum_{i=1}^{I^e} q_{it}^e$ equals a target amount Q^e_{target} of the bioenergy product. The corresponding size of the production area Y_t can be evaluated with Eq. (4), to compare the potential size of policy areas. Finally, the subsidy is optimal when the marginal gains to society from subsidizing the least efficient plot j equals zero $\omega_j^e = 0$. That is where the marginal social benefits equal the marginal net costs of subsidizing. Since S_j^c is fixed, we can calculate the value of S_i^e that corresponds to the optimum subsidy pattern.

3.3. Modelling production quantities

We propose to approximate the output vector of products with crop-specific yield values, which can be directly mapped from local biophysical features. We model the yield following [60] by attributing crop-specific damage scores related to drought Rd and water-logging Rw according to the local combination of geological and hydrological conditions. The damage scores are designed to be used with the yield function below to calculate the crop-specific expected yields.

$$q_{it}^l = \varphi_{it}^l q_{it,max}^l \quad (12)$$

$$\varphi_{it}^l = 100 - Rw_{it}^l + Rd_{it}^l\left(\frac{(100 - Rw_{it}^l)}{100}\right) \quad (13)$$

The production quantity vector for a specific land-use type in the choice model of Eq. (1), q_{it}^l, is the crop-specific maximum attainable yield, $q_{it,max}^l$, multiplied by φ_{it}^l, that is, the local yield conditions factor ranging from 0% to 100%. This procedure to quantify expected yields has been successfully applied to model a variety of crops in studies for the Netherlands [40,63] and Argentina [16]. In a similar NPV framework [13] were able to replicate national agricultural land-use patterns in the Netherlands with 84% degree of correspondence on a pixel by pixel comparison.[6] This shows that Eqs. (1) to (3) in combination with Eqs. (12) to (13), is not just practical but also appropriate to simulate land use.

4. The case of miscanthus in the netherlands

We illustrate our approach to accounting for spatial heterogeneity in bioenergy stimulation policies with an application to a second-generation perennial biofuel crop - Miscanthus - in the Netherlands. The Netherlands is selected as a study area for several reasons. First, it has an advanced agricultural sector with high economic value per hectare and a high population density. Consequently, there is high pressure on land for both urban land uses and intensive agricultural activities, resulting in strong competition between different types of agricultural land use [39]. Because of this competitiveness, there is no unused marginal land in the study area, so we do not need to account for potential variability in the supply of agricultural land conditional on marginal changes in subsidy patterns.[7] Second, application of our model in the Netherlands allows us to investigate whether possibilities for Pareto improvements in current subsidy schemes are substantial even in a small, and highly competitive agricultural system. Moreover, the small size of the country has the advantage that we can assume biofuel prices to remain stable when production volumes increase; the additional production is not likely to influence these prices that follow supply and demand conditions at far larger scales. The Dutch case is also interesting for policymakers, as it is an example of a country that is still far behind current national and European ambitions for sustainable energy, and that lacks a developed agricultural production system for second-generation biofuels.[8] Miscanthus was chosen for our case study because different studies describe it as potentially high yielding [20,65,64]. [63] show that Miscanthus is more economically viable than sugar beets for ethanol production, validating the usefulness of Miscanthus as a non-food biofuel source. Bearing in mind the arguments put forward by different critics of food-based biofuel [32,58], Miscanthus could thus be of particular interest for energy production from an ethical point of view.

Agricultural land use in our study area mainly consist of two dominant production systems, arable farming and dairy farming, both modelled with different rotation schemes for sand and clay soils. For arable farming our model is made operational by using prices and values described by [14] for in- and output vectors p_{it}^c (prices for agricultural products), $q_{it,max}^l$ (maximum attainable yields), h_{it}^l (the types and amounts of production inputs), w_{it}^l (the prices of the various inputs), k_{it}^l (fixed costs including start-up investments and equipment costs), and o_{it}^l (the farm operation costs). The product prices are updated using 5-year averages of the product prices reported by [41].[9] Local production quantities q_{it}^l are obtained by transforming the maximum attainable yield

[5] Combining Eqs. (6) and (7) leads to $\check{S}_n^e \le \bar{S}_n^e$, with $\check{S}_n^e < \bar{S}_n^e$ if there is variation in $\Pi_i^c - \tilde{\Pi}_i^e$ across i. Therefore, $\Omega^e(\check{S}_n^e) > \Omega^e(\bar{S}_n^e)$ follows trivially under heterogeneous production factors.

[6] Weighted average, making use of the fact that 69.1% of agricultural land is dairy farming, and there was 90.1% degree of pixel by pixel correspondence for dairy farming and 71.7% for arable farming.

[7] An overall decrease in land supply due to ongoing urbanization is more likely and could be incorporated in our approach but we exclude this as well as it is not likely to change the competition between different types of agricultural land use, but would only adjust the total amounts per types.

[8] In 2012, 3.4% of fuel sold in the Netherlands originated from first and second generation sources and only 20% of these source materials were produced in the Netherlands [19]. The main sources for second-generation biofuels of Dutch origin were domestic garbage, recycled fats and tallow.

[9] The 10-year averages for potatoes.

quantities $q^{l}_{it,max}$ using yield factors φ_i^{l} estimated using data on local soil and hydrological with Eq. (13), assuming that these factor remain stable over time.

Since dairy farming operations do not directly sell grass, but rely on its yield as an input in milk production, the economic assessment of this production system relies on additional intermediate steps. Production quantities, and yield related costs, for dairy farming operations are modelled based on the assumption that cows require energy, supplied by grass, to produce milk. The energy (grass) supply is linked to local grass yields φ_i^{grass}. Energy shortages are computed at each yield level to obtain the amount of required supplementary energy. We assume that farmers supplement their grass supply with silage maize according to local energy shortages and the digestable energy content of silage maize. Silage maize is bought at opportunity costs since maize is grown in rotation, reflecting the costs of not selling it on the market. Milk is sold as the main product at similar 5-year average prices reported by [41], and excess silage maize is sold as a secondary product. Further details regarding the calculations are contained in Table CI in Appendix C.

Specifying the production conditions for Miscanthus is more complex as less documented experience is available. Soil and groundwater related yield reduction values, for example are not available for Miscanthus. This void was filled by relying on the expected local yield values from [63]. Also, a market price for Miscanthus is not available as the market is undeveloped. We account for that by using a price range based on imported lignocellulosic biomass prices, averaging €3.25/GJ for pellets from Latin America, €4.50/GJ for pellets from Eastern Europe, and €5.50–6.50/GJ for pellets from Scandinavia [34] and converting biomass to lignocellulosic energy equivalents (see Appendix A). Recent projections on the development of the biofuel sector taking into account the 2014 drop in crude oil prices, indicate that in the short to medium-term, high energy prices and high investments that could possibly lead to improved conversion rates are unlikely [44]. We use data on the conventional subsidies s_{it}^{c} that are distributed in the European Union. Depending on the land-use type, farmers in Europe receive income support of up to €446 per hectare per year in the Netherlands according to the CAP [22]. Since the 2003 CAP reform, subsidies of €45 per hectare per year are available to farmers growing energy crops for 70% of their lands deployed in energy crop farming [21].[10]

We combine all prices and other production-related values and insert them in Eq. (1) to compute the economic profitability of land at each individual grid-cell. To construct a spatial distribution of conventional land-use profits Π_i^{c}, we link conventional land-use vector $l=c$ to agricultural land-use data [43] registered at the parcel level. Since the land-use data set reflects the situation at a fixed moment in time, crop cycles are implemented to simulate the average NPV of various crop rotation schemes throughout a period of 20 years.,[11,12] We take a weighted average of profits according to the share of each crop type in a crop rotation.

By Eq. (6), homogeneous biomass subsidies are determined by the size of the policy area through the inverse mapping of Eq. (4). We link $Q^{e}_{t,target}$ in our model to the required growth in bioenergy production to meet the bioenergy market share targets set by the European Union for 2020 and accordingly determine the required production area that provides the basis to determine the minimum homogenous subsidy.[13] The benefits of emission savings per unit of biomass product ε^{e} are the amount of fuel savings based on the European reference of 88.3 kg CO2eq/GJ [19] per energy unit multiplied by a carbon price p_{ε} of €20 per ton. The carbon sequestration benefits σ_{it}^{e} of Miscanthus are based on 8.8 tons CO2eq reported by [9]. Arable crops in our rotation schemes do not consist of perennial crops and are assumed to store no significant amounts of carbon in their root systems. Though we are aware of opportunities for carbon sequestering in the dairy farming sector, we omit them from our analysis as they are too strongly dependent on site-specific practices Fig. 1.

5. Results

5.1. Economic performance of production systems

Fig. 1 presents our assessment of the economic performance of various crop cycles in the Netherlands for declining soil suitability. A brief discussion of the robustness of the results, along with the distributions of estimated economic performance Π_i^{l}, is provided in Appendix D. On average, clay soils perform better than sandy soils for both arable farming and dairy farming. The economic performance of arable farming is more sensitive to yield values than that of dairy farming. This results from the ability of dairy farmers to import silage maize when the grass yields on their specific plots are modest and still make profits on the sales of their final products. Miscanthus is more sensitive to yield than dairy farming, but less than arable farming Fig. 1.

Fig. 1 [14] provides important insights into the general trend of land-use competition between Miscanthus and conventional crops.[15] Arable farming receives high income support through the CAP and requires high soil suitability to be profitable, as Fig. 1 shows.[16] The NPV of dairy farming is less sensitive to change in obtainable yield, and its occurrence is centred mainly on lower suitability soils because arable farming outcompetes dairy farming on high yielding soils. Dairy farming simultaneously is less subsidized. This causes a self-selection process in which areas with productive soils receive higher subsidies while areas with low suitability intersect with land-use types that receive less financial support. The implications for bioenergy production are that the opportunity costs of producing Miscanthus increase on more productive soils, because: 1) high-suitability areas self-select into areas that receive higher income support, and 2) high soil suitability is relatively more in favour of the economic performance of arable farming than that of Miscanthus.

5.2. Assessing the impacts of different policies

Fig. 2 shows how different subsidy schemes that reorder the sequence in which production sites are subsidized, produce differently shaped social cost and benefit curves. Single focus

[10] This subsidy system is one of the oldest European policies and is still gradually being transformed. The total expenditures on CAP have declined in the past decades. In 2011, the total CAP expenditure accounted for 44% of the total European budget, while in 1986 this was around 75%. Nevertheless, the CAP remains an important source of income to farmers.

[11] We use an inflation-adjusted discount rate of 3%.

[12] The rotation scheme that we use is contained in Table BI in Appendix B.

[13] All data and assumptions regarding energy usage are contained in Appendix A.

[14] The total amount of locations with a negative NPV accounts for only 2.6% of agricultural land. Possible explanations are discussed in Appendix D.

[15] Plot-specific deviations from the general trend in land-use competition are possible as the yields of dairy farming production systems and arable farming production systems are not perfectly spatially correlated. The spatial analysis, on which subsequent sections build, takes this into account but is difficult to generalize here. The Histograms in Fig. D1 in Appendix D show the factors used in Eq. (7) to model the spatial comparison between Miscanthus and conventional land-use profit levels. The map in Fig. E1 in Appendix E shows the resulting spatial distribution of the minimum required subsidies.

[16] Not deducible from Fig. 1, the CAP support includes limited support for dairy farming production systems through subsidizing maize production, which is a small percentage of the rotation system. Arable farming production systems receive direct income support for a large part of their rotation scheme.

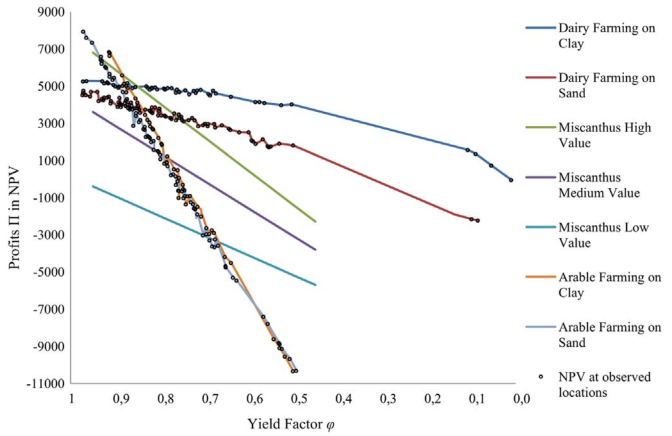

Fig. 1. Economic performance in discounted euros per hectare of different production systems at declining yield levels. [14] Soil and groundwater table combinations that lead to a Miscanthus yield higher than 0.95 or lower than 0.45 are non-existent in the Netherlands. Dots represent observed combinations of soil types and ground water tables, lines are linearly interpolated.

schemes (SFLB and SFPB) tend to misallocate funds as can be seen from the erratic cost curves. Integrated agricultural focus schemes (IAFLB and IAFPB) that take into account the way in which conventional subsidies S_i^c are allocated, have smoothened cost curves and a larger integral area between the social cost and benefit curves. Targeting production sites by production based opportunity costs instead of land based opportunity costs generates cost curves that are very similar, and efficiency differences are not directly apparent from the cost curves only. Policy that aims to minimize land-use change, results in a cascading succession of "separate" cost curves for regimes with similar biophysical conditions, as each biophysical regime includes production sites with low and high social costs.

Fig. 2 finally also shows that with high market prices, marginal costs and benefits have only a few intersections clustered at a high percentage of land deployed for Miscanthus production. When market prices are low, there are however numerous intersections spread out over a large part of the graph area. This implies that the effect of spatial heterogeneity on the relative performance of SF and IAF schemes varies strongly depending on the market prices

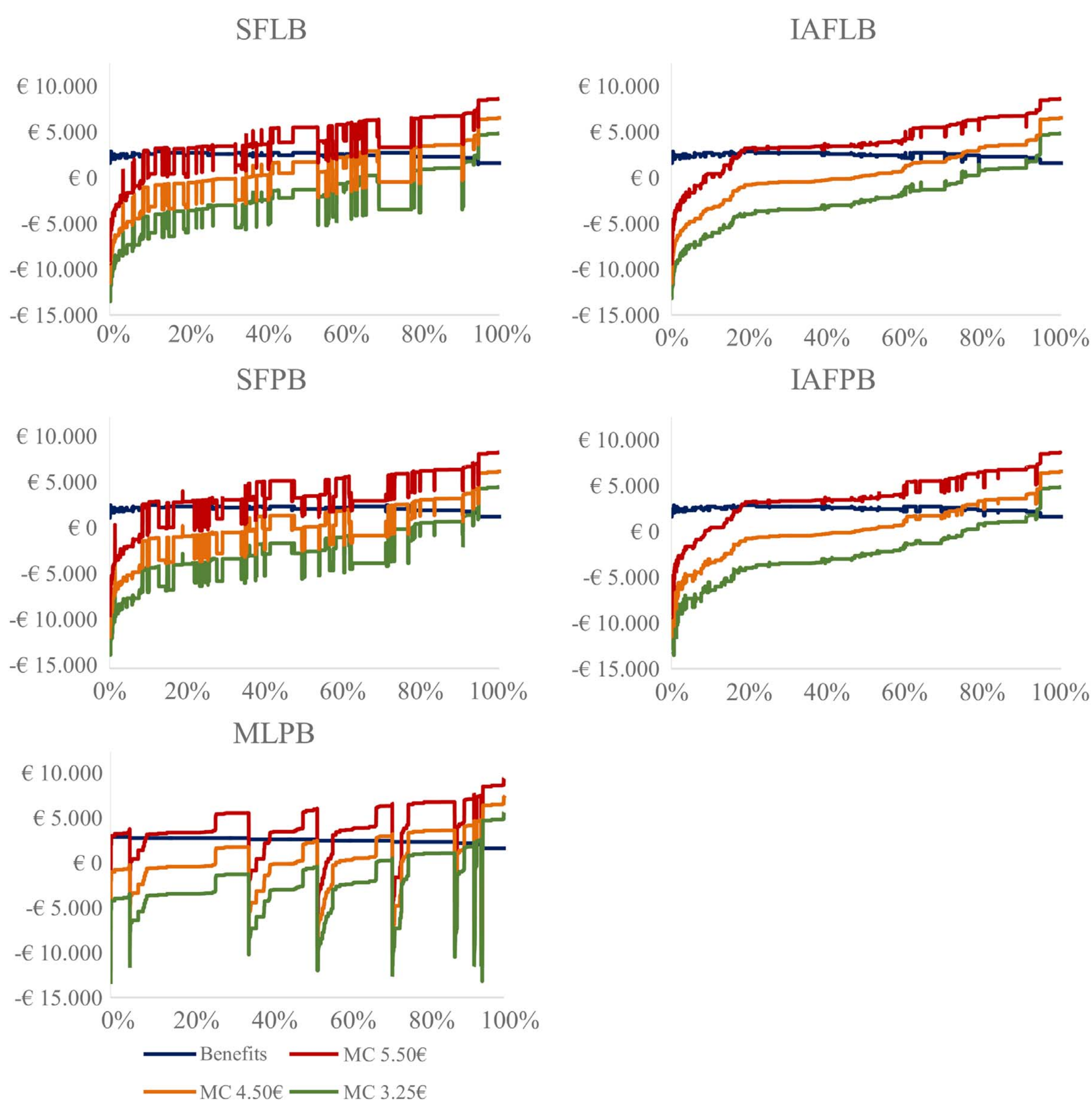

Fig. 2. Discounted social marginal cost MC (C_i^e) and social marginal benefit MB (B_i^e) curves for the five heterogeneous subsidy schemes. Single focus schemes follow the private opportunity costs for Miscanthus production, Integrate Agricultural Focus schemes follow social opportunity costs by taking into account the current allocation of conventional subsidies, ML minimizes land-use change. LB and PB stand for land based and production based schemes respectively. Horizontal axis is the percentage of total agricultural land deployed for Miscanthus production.

for bioenergy crop material. The main implication is that when market prices are low, and subsidy requirements are high, it pays more to subsidize the right plots first.

5.3. Comparing different policies

The relative performance of different heterogeneous policies varies with production total. Using Eq. (10), the total net benefit potentials are calculated for the entire range of potential production sites.

Fig. 3 depicts the course of potential net gains for an increasing total production area under different heterogeneous schemes. As the total area targeted by the policy increases, the curves diverge as spatial heterogeneity in the targeted area increases. When the total area targeted by the policy nears 70% of the entire region, the total net benefits under different heterogeneous schemes converge; when all the farmers within a region receive funds, the order of fund allocation or the selection of plots that receive funds within the region does not matter. The largest difference between

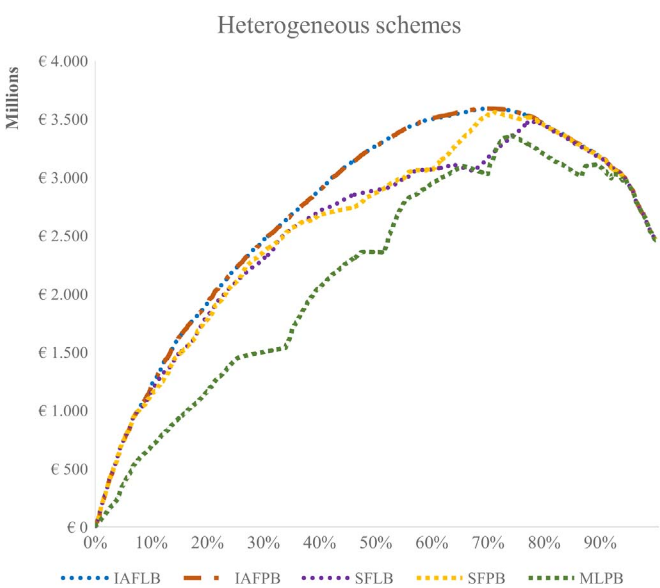

Fig. 3. Total discounted net benefits in euros for heterogeneous subsidy schemes with bioenergy market prices of €4.50/GJ. Horizontal axis is the percentage of total agricultural land deployed for Miscanthus production.

IAF and SFLB schemes at €4.50/GJ occurs near a conversion rate of 68% of the region. At this point, potential net benefits of IAF schemes are 17% higher. At €4.50/GJ the differences between heterogeneous schemes are not very impressive, each policy has its own optimum and these optima produce relatively similar net benefits. But Fig. 3 clearly shows an important aspect of heterogeneous schemes, the foregone benefits of second-best heterogeneous schemes are approximately hyperbolic with the rate of land-use conversion or aggregate subsidy spending.

To investigate further how different heterogeneous schemes compare, we repeated the analysis for a range of bioenergy prices with €0.10 increments. We compare the different policies to obtain information on the overall convergence or divergence in performance of the different policies when prices for bioenergy change. For robustness, we are interested in comparing the performance of policies when each policy is evaluated at its optimum and when policies are evaluated at the point where they differ the most in terms of efficiency. Therefore we computed two statistics for each price level: I) the percentage difference between maximum net benefits, evaluated for each policy at its respective optimum, and II) the percentage difference between net benefits, evaluated at the widest gap between the benefit curves. We benchmark the policies against the SFLB scheme to see how integrated and production based schemes compare to land based heterogeneous schemes. At low market prices, the second measurement is associated with negative SFLB benefits. For these cases, relative differences are computed using an absolute valued denominator.[17]

Fig. 4 shows that the relative difference between net benefits, according to both measurements, varies strongly with bioenergy prices. Ordinal performance stays, however, relatively stable over the evaluated price range. IAF schemes, measured at both optima and widest gaps, perform better than SFLB schemes, while the MLPB scheme performs less. At the lowest evaluated price, the SFPB scheme in optimum, performs less than the SFLB scheme in optimum. It performs however better at low to mid-range prices. When relative performance is measured at the widest gap between the net benefit curves, the production based version of single focus schemes performs better at any evaluated price level. The largest relative differences in optima occur at low bioenergy prices. A striking feature of 4I and 4II is the large spike around a bioenergy price of €3.65/GJ. At this price, evaluated at its optimum, the SFLB scheme is close to the social break-even point. This results in high relative differences. As prices increase, both Figs. 1 and 2 show a convergence of heterogeneous schemes. The general trend of high differences at low prices and convergence at higher prices, can be attributed to an interaction between spatial heterogeneity and bioenergy prices. When bioenergy prices are low, many plots require a subsidy. There are initially high relative rewards for subsidizing the right plots. When prices increase, fewer plots require subsidy, and subsequently there is less heterogeneity in the remaining plots that require aids.

To investigate the potential benefits of implementing spatial variation in subsidy schemes, we compare the relative performance against spatially homogeneous subsidies aimed at reaching the European 2020 fuel standards.[18] Fig. 5 depicts net potential benefits associated with both heterogeneous and conventional schemes. Conventional schemes are clearly less efficient but outperform the MLPB scheme. At 17 PJ, IAF schemes produce 28% more gains than conventional land based subsidies. The net benefit curves of conventional schemes in Fig. 5 are less steep at the 37 PJ production total than for the 17 PJ production total. This is in line with what was derived analytically from our model, the marginal increase in aggregate subsidy spending between the homogeneous schemes and heterogeneous schemes diverges as the policy area increases. At the same time, at 37 PJ, an IAF scheme increases net benefits with 20%, slightly less than at 17 PJ. This means that, while overfunding related to homogenous subsidies increases, there is a sharper decline in the marginal benefits of IAF schemes. For the transition of 17 PJ to 37 PJ, the decrease in the marginal potential net benefits is thus stronger than the increase in the forgone benefits of conventional schemes.

The increase in foregone benefits under conventional schemes, however, has strong implications for environmental policy. When conventional schemes are in place and international agreements become more ambitious - energy targets are replaced with more ambitious ones - subsidy schemes need to adjust to generate the increased supply required. This means that all periodical aids are required to increase to the level where additional farmers, with

[17] As: $(Alternativescheme - SFLB)/|(SFLB)|$

[18] European fuel standards can be reached with further growth of first-generation biofuel crops, in which case a total production of 17 PJ of second-generation biofuels is required, or without further growth in first-generation biofuel crops, in which case 37 PJ is the required production growth. See Appendix A for details on the construction of these figures.

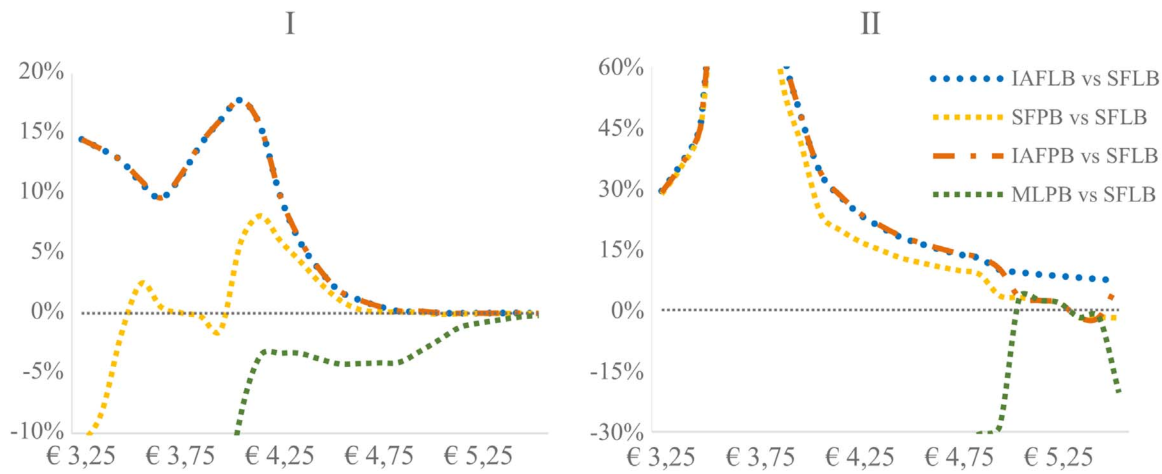

Fig. 4. Relative net benefits of heterogeneous schemes compared to SFLB schemes for a range of bioenergy prices depicted as; I) the percentage difference between the optima of different policies, and II) the percentage difference evaluated at the widest gap between the potential benefits associated with the different schemes.

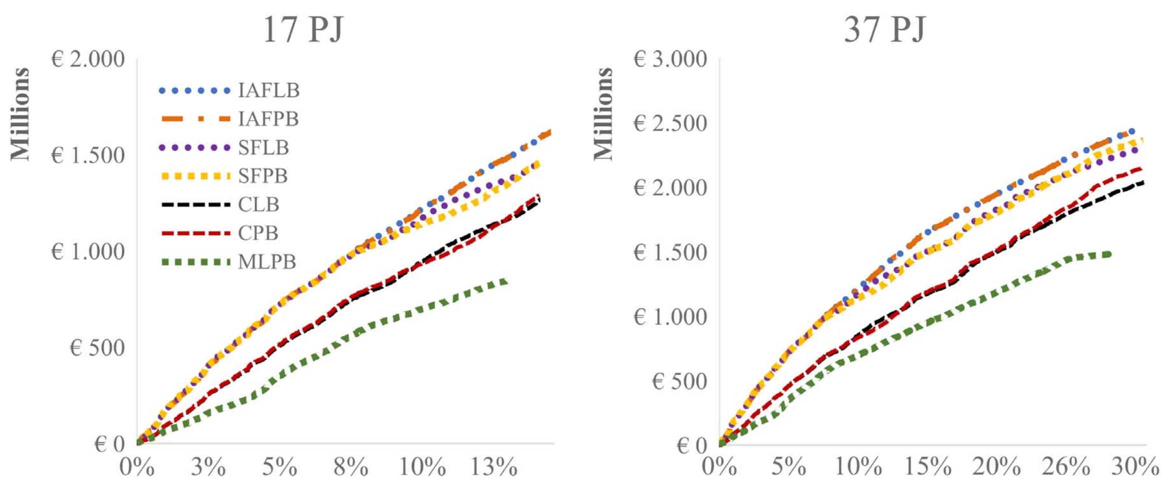

Fig. 5. Aggregate discounted net benefits in euros for each subsidy scheme with bioenergy market prices of €4.50/GJ.

higher opportunity costs, will contribute to bioenergy production as well. The implication of having conventional schemes in place is that it can form a disincentive for engaging in new and more ambitious agreements. The results show that this effect might even be slightly stronger for land based schemes than for production based schemes. Under a conventional policy, at 37 PJ, production based schemes have 5% higher potential net benefits than land based schemes. At 17 PJ, the difference is only a 2%.

The analysis also shows that minimizing land-use change comes at relatively high costs. At 17 PJ, the potential gains are 33% lower than those of IAF schemes, while the total land-use change is reduced by around 11%. At 37 PJ, the gains are 27% lower while the total land-use change is reduced by only 5%. In both cases, we do not account for possible benefits of minimizing total land-use change, but the results imply that these have to be substantial if MLPB schemes are preferred over IAF schemes. If the MLPB scheme is, however, benchmarked against conventional schemes, the additional required benefits from minimizing the land-use change need to be substantially smaller.

Final analysis shows that the results are robust to a range of different prices. At both 17PJ and 37PJ we repeated the analysis with €0.10 bioenergy price increments and noted the percentage difference between alternative subsidy schemes and CLB schemes to see how heterogeneous schemes compare to conventional schemes depending on bioenergy market prices. Fig. 6 shows that the alternative schemes are especially more efficient when bioenergy prices are low.

We can observe from the graphs that the initial differences in relative performance of alternative schemes at low prices, are higher for increased total bioenergy production. The rate at which the curves converge is however also higher at increased total production. Whether the relative performance of heterogeneous schemes improves when bioenergy ambitions go up, thus depends on the market price of bioenergy at which policies are evaluated. This nonlinear effect is due to the net effect of a trade-off between spatial heterogeneous interactions. When bioenergy prices are low, a large amount of plots require subsidy and subsequently the heterogeneity in subsidy requirements is high. Furthermore, when total bioenergy production increases, more plots are required to reach the target aggregate production quantity and heterogeneity within production sites increases. Together, low prices and larger aggregate production thus result in a high level of heterogeneity due to increased heterogeneity in subsidy requirements and additional heterogeneity due to the extended set of production sites required to reach total production quantities. If, however, bioenergy prices increase, heterogeneity in subsidy requirements decreases as the amount of plots that require subsidy decreases. Heterogeneity decreases disregarding aggregate production quantities, but the plots that will no longer require financial support at elevated prices, make up a larger share of the production sites at 17PJ than at an aggregate production quantity of 37PJ. As an effect, the relative gains of preventing excessive funding of

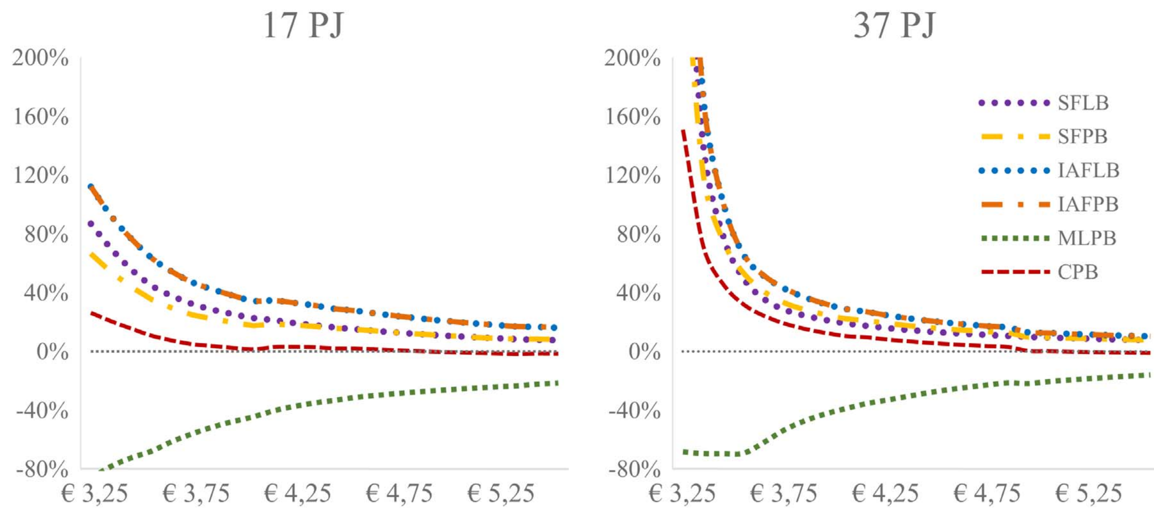

Fig. 6. Total net benefits of different schemes at bioenergy production levels of 17PJ and 37PJ.

plots at high prices, is larger at low production quantities, and heterogeneous schemes perform relatively better at lower total production if bioenergy prices are high. Disregard of this complexity, IAF schemes are clearly more efficient than conventional schemes at any price for both aggregate production totals, and MLPB schemes are relatively costly to society.

6. Discussion and conclusions

In this paper, we explored the role of spatial heterogeneity in biofuel stimulation schemes. Under heterogeneous subsidy allocation, we find that the potential gains from stimulating Miscanthus production are distributed according to the differences between potential private profits and potential net social benefits. The efficiency of a heterogeneous allocation is therefore strongly determined by the order at which sites are targeted. We considered three types of heterogeneous schemes: 1) single focus schemes that allocate subsidy based on private opportunity costs, 2) integrated agricultural focus schemes that additionally take into account how conventional agricultural subsidies are distributed, and 3) a scheme that minimizes land-use change. First, our results show that conventional subsidy schemes that allocate a fixed amount of funds on a per-hectare basis, tend to overfund a large part of the farmers who engage in biomass production, and that under heterogeneous stimulation schemes, there is scope for Pareto efficient improvements with respect to current subsidy spending. While heterogeneous schemes minimize overfunding, they may misallocate funds. Our results show that a scheme that targets plots based on the expected yields of bioenergy crops, is less efficient than conventional stimulation schemes in reaching the 2020 mandate. We find that schemes that follow private opportunity costs misallocate funds due to the heterogeneity in both external benefits of produced carbon offsets and the potential to reduce conventional agricultural subsidies. The foregone benefits of non-optimal heterogeneous allocation is hyperbolic with total land conversion. It is found that integrated agricultural focus schemes optimize benefits by reducing the conventional subsidy for other agricultural activities, minimizing social costs of sustaining biofuel stimulation and minimizing both overfunding and misallocation. Alternatively, one can view the differences in efficiency between single focus and integrated schemes not as properties of the schemes, but of subsidies that are currently in place for conventional agricultural activities. The differences between heterogeneous schemes are fairly small at higher bioenergy prices, but increase substantially in the lower range. At high prices, many sites do not require a subsidy, and there is less heterogeneity among potential production sites. The link between the relative importance of heterogeneity and energy prices is important considering the 2014 oil price drop. Second, we show that under both single focus schemes and conventional schemes, production based payments generate better results than land area based payments. Again these differences are small at high bioenergy prices, but increase in the lower range of energy prices. Third, under heterogeneous schemes, the marginal costs of engaging in more ambitious environmental agreements follow only site-specific social costs, while under conventional schemes they increase rapidly due to increased overfunding of farmers that have lower minimum subsidy requirements. The most substantial increase in net benefits can be achieved when market prices for bioenergy are low and environmental targets are ambitious. This is an important finding and stresses the relevancy of spatial heterogeneity for policy since many countries struggle with meeting their ambitious objectives under current energy prices.

Our results add to the discussion around carbon contracts. In recent years, agreements such as the Kyoto Protocol and the recent

Paris agreement, have encouraged the global economy to collaborate in creating emission trading markets. While the recent agreement did not specify a global carbon price, it does recognize its importance for providing incentives for emission reduction activities. Furthermore, it mentions result based payments as an important way to provide incentives for emission reductions. It appeals to suggest that biofuel stimulation policies could be improved by capping and trading. Supporting farmers through this system can address problems related to the cost-efficiency differences arising from spatial heterogeneity and shift biofuel production to farmers that face favourable production characteristics. The cost effectiveness of cap-and-trade has been widely discussed already in the 1970s regarding air pollution policies [8] and more recently concerning agriculture. Specifically, it has been shown that cap-and-trade programmes outperform tax-based policies [4]. A large body of literature on carbon sequestration also supports integration with cap-and-trade [45,46,2]. In fact, our results corroborate that homogenous production based schemes are more efficient than per-hectare payments. Especially at the lower range of evaluated prices this improvement is substantial. However, a problem related to the implementation of carbon sequestration contracts is the high costs of quantifying the amount of sequestered carbon at every production site [56]. Obstructions of this kind seem less stringent in the case of contracts for biomass production, as the output of these activities can be more easily measured since it is primarily the final product itself that contributes to emission savings. This suggests that there is a strong case for policy targeting to reduce emissions by capping and trading. However, our study reveals that the integration of biofuel production into cap-and-trade by providing emission offsets remains prone to inefficiencies that arise from spatial heterogeneity. The results show that conventional production based schemes over- and misallocate funds, and schemes that explicitly address the heterogeneity in subsidy requirements, and possibly in the distribution of externalities, increase benefits substantially. Especially when total production of emission offsets increases, and market prices for bioenergy are low, the amount of foregone benefits sum up considerably.

This study contributes to the general debate on the potential contribution of the agricultural sector in reducing emissions, by offering insights in more efficient stimulation schemes. Prior to implementing such policies, more extensive cost-benefit analysis that accounts for additional factors influencing local production potential is needed. We suggest some extensions to the framework presented in this paper. One potential drawback of our pixel-by-pixel approach is that sites are treated as *identically and independently distributed*, while in reality farmers typically manage several sites under a single budget construct and can be expected to make managements decisions based on returns to the whole farm operation. On a related note, our approach does not account for economies of scale or risk aversion. As prices and yields are stochastic, profit, or expected value, maximization might deviate from the true objective function of a risk-averse farmer. In this case, the correct objective function will instead maximize expected utility of profit, which could result in portfolio diversification. Risk is however not only related to volatility of market prices and yields, but also to irreversibility of some investments. While NPV methods are an established method for land-use valuation, there is a wide range of literature citing weaknesses that relate to this type of risk. NPV methods treat investments as a onetime only opportunity [17], based under assumptions concerning future cash flows under a static investment strategy that a firm starts and completes as planned [66]. It is more realistic however to subscribe to the idea that investments become less risky into the future as the information set on which decisions are based grows, and that information can alter investment strategies along the way as it becomes available. For most investment strategies, the horizon is relatively short, as in our application, and the effect may not pose a significant problem [48]. But in the case of bioenergy, for which a fully developed market does not exist, uncertainty regarding future cash flows is high. While the production of a perennial crop like Miscanthus allows very limited altering of the investment strategy along the way, irreversibility can be expected to play an important role in adaption and a better approach would be to explicitly balance the benefits of immediate investment to those of waiting in to reduce risk [47]. Furthermore, our analysis showed that arable farming, Miscanthus production, and dairy farming, (here ordered by declining sensitivity to yield) all have a distinct sensitivity to yield. Risk due to stochastic yields will therefore have a distinct impact on the expected utility of profit for each land-use type.

Improving the level of detail in the assessment by incorporating the notions described above will certainly result in a more precise analysis. However, while the addition of these complexities will impact the exact amounts of subsidies required to initiate bioenergy production, we expect our general conclusions to hold as these do not depend strongly on the accuracy of point estimates, but on the ordinality of efficiency results of different schemes, which are shown to be robust for a range of different prices. Future research might consider Real Option Value methods to explore the impacts of heterogeneity under risk and irreversibility of investments (see [50] for more extensive discussion), and agent based models to explore the impact of moving towards more detailed representations of farm operations.

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Appendix A. Energy data

Table AI
Input data on the energy-related variables applied in this study.

Variables	Values
Required biofuel consumption in transport	611 PJ[1]
Miscanthus lignocellulosic energy content	5.95 GJ[2]
First-generation biofuel used	14 PJ[3]
Second-generation biofuel used	7 PJ[3]
Weighing factor first-generation fuel	1[4]
Weighing factor second-generation fuel	2[4]

[1] 10% of the total energy used in the transport sector [23].
[2] 35% lignocellulosic energy conversion taken from [63], 17 GJ energy per oven dry ton taken from [7].
[3] [19].
[4] [19], only half of bioenergy production may be food-based.

Appendix B. Crop rotation schemes

Table BI
Crop rotations for the two major production systems in our study, specified for soil types.

Arable farming	Clay	Sand
Ware potatoes	17.09%	15.06%
Seed potatoes	13.03%	4.07%
Starch potatoes	0.33%	29.30%
Beets	16.10%	21.06%
Winter barley	0.77%	1.42%
Summer barley	2.74%	12.31%
Winter wheat	46.66%	10.27%
Summer wheat	2.85%	5.19%
Fallow	0.44%	1.32%
Dairy farming		
Grass	89.0%	70.0%
Silage maize	11.0%	30.0%

Appendix C. Modelling the dairy farming production system

Table CI
Variables and values used to model local production quantities.

Variables	Values
Average number of cows per hectare	2.1[1]
Average litres of milk per cow	8147[2]
Energy need per cow per day	Modelled[3]
Digestible energy content of feeding material	11.6 MJ per kg[4]
Grass supply	Modelled[5]
Costs of silage maize	Opportunity costs
Field operation costs	Same as for grass[6]
Other animal costs (healthcare and breeding)	€189 annual, per cow[7]
Milk processing costs	€0.21 per litre[8]
Herd investment costs	€ 895 per cow[9]
Average lifetime of cow before replacement	5 years[10]

[1] based on figures from [41], 2.1 is slightly above the national average of 1.9 but below some locally observed values, which go up to 2.6.
[2] based on figures from [41].
[3] modelled following [6].
[4] per kg oven dry grass and pelleted whole plant corn, taken from [54].
[5] modelled per month following the method by [10] and rescaled using local yield values.
[6] taken from [63].
[7] adjusted for inflation and tax, based on 3-year company survey performed by PPP Agro Advice [11].
[8] from [24].
[9] four-year average price of two-year-old calf [41].
[10] from [33].

Appendix D. Frequency distribution of agro-economic performance

According to our estimations, the frequency distribution of the NPV of observed land use is left-skewed with a small number of production sites facing losses. Several factors may explain this outcome: 1) our estimation is negatively biased; 2) farmers possibly speculate on product prices and current land-use types generating long-run losses are profitable in the short run; 3) plots that face negative NPV benefit from unobserved comparative advantages such as regional specializations; 4) farmers do not fully take into account in their decision process all the costs that are included in our assessment; and 5) the agricultural sector is not fully in equilibrium because of a high elasticity of land-use change. The aggregate amount of production sites with a negative NPV is, however, small and the overall distribution centres densely closely above zero, which is likely in a competitive market.

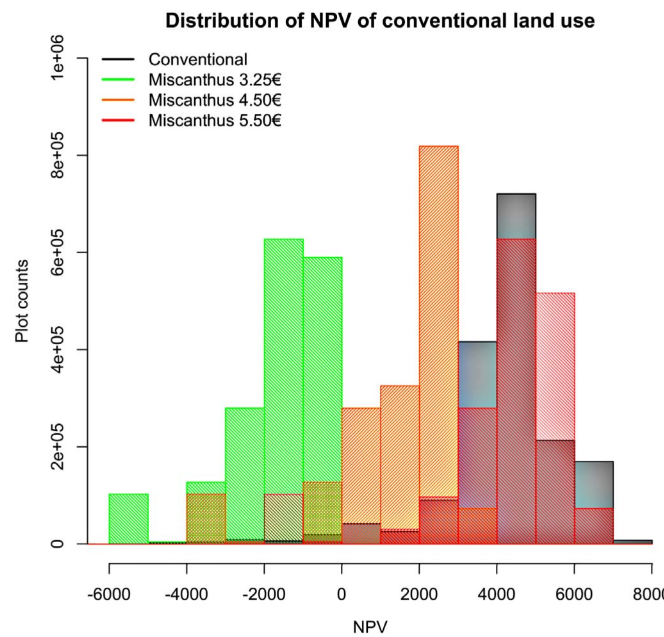

Fig. D1. Distribution of the economic performance of the agricultural sector and Miscanthus in the Netherlands.

Appendix E. Spatial distribution of minimum required subsidies

The map shows the considerable differences in minimum

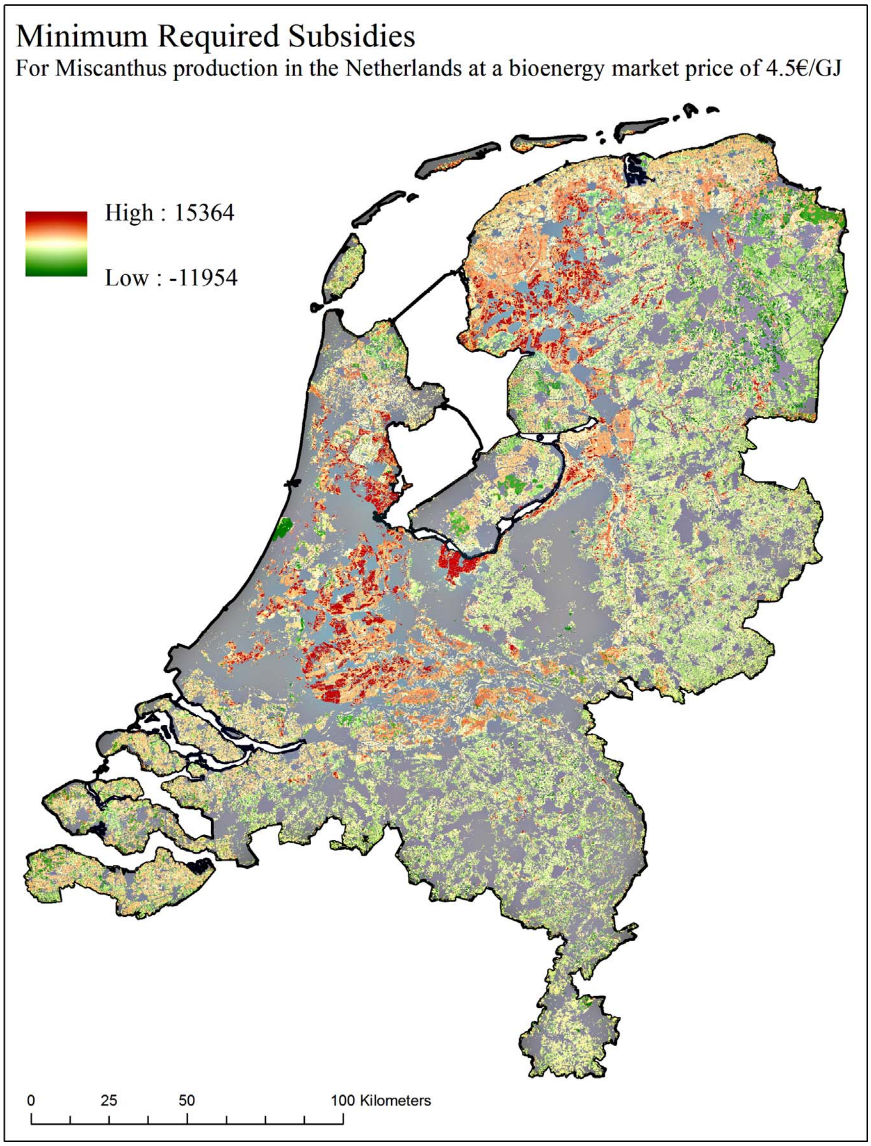

Fig. E1. Spatial distribution of minimum required subsidies in the Netherlands.

required subsidies for bioenergy production. Clay soils, located mainly in the west of the Netherlands, perform economically better than the sandy soils, located in the east and north of the Netherlands. Clay soils coincide with areas where the minimum required subsidies for Miscanthus production are higher.

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